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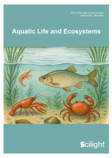

Article

A Novel and Non-Invasive Approach to Estimate Abalone Biomass Using Image Analysis

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Abstract: Physical removal of abalone from the attached substratum for biomass assessment can cause stress, physical damage or even death. This research aims to develop and test 3 models using an image-based method to accurately determine weight and length for 3 age classes of cultured abalone. Abalone were grouped into three size classes (1, 2, and 3 years old) for photography. Photos were analyzed using image processing. The extracted data were used to develop the prediction models and perform a validation test using an independent dataset. In the 1-year-old group, the quadratic model was a fitted regression for estimating the weight of abalone based on the image of the shell, using shell length as the predictor. In contrast, the power model was able to accurately predict the weight using the shell area. In the 2-year-old group, the lowest estimation error values were observed using the shell area quadratic model. The quadratic model was better at predicting abalone weight from either image-based shell length or shell area in the 3-year-old group. The power regression model exhibits better performance in weight estimation, regardless of abalone size, using the image-based shell length. Either the quadratic model or the power model can be used to estimate the weight of farmed abalone using an image-based shell area. Our results indicate that the success of image analysis technology to estimate abalone mass could reduce negative impacts on abalone during biomass determination and contribute to the efficiency of management in abalone farming. The models could potentially be applied in stocking assessment work with some modifications.

Keywords: abalone; image processing; biomass estimation; regression models

1. Introduction

Abalone (*Haliotis* spp.) are gastropod molluscs in the family Haliotidae. They are one of the most expensive seafoods in many parts of the world due to their high nutritional value and health benefits to humans. Abalone is a rich source of polysaccharides, proteins, lipids, essential fatty acids, amino acids, and various bioactive compounds with antioxidant, anti-thrombotic, anti-inflammatory, antimicrobial, and anticancer properties, providing health benefits beyond its nutritional value [1]. Recently, wild abalone populations have declined significantly due to overexploitation, illegal catch, disease, and habitat degradation [2,3]. A decrease in fishing, combined with high global demand for abalone, has created an opportunity to establish aquaculture farms to meet the abalone market needs [2,3]. This has resulted in a significant increase in abalone farms and overall production globally [3,4]. Between 2002 and 2010, abalone production on farms increased by more than 7.5 times, and worldwide production reached over 65,000 metric tons in 2010 [2]. It gradually increased by 158% from 2010 to 2013, reaching 103,464 Mt [2], and approximately 160,662 Mt in 2016/17 [3]. The vast majority was produced in Asian countries such as China (139,697 metric tons, Mt) and South Korea (16,042 Mt). Other important farmed abalone producers are in South Africa (1,685 Mt), Chile (1,468 Mt), Australia (960 Mt), Mexico (23.5 Mt), Taiwan (300 Mt), and New Zealand (60 Mt) [3]. Recently, the global farmed abalone production reached 243,506 Mt in 2020/21. China (217,431 Mt) and South Korea (20,053 Mt) remained as the top and second largest producers. [4]

In an aquaculture setting, regular assessing abalone biomass is necessary to determine daily feed intake and avoid under or overfeeding [5], adjust stocking density, grading, and controlling water quality [6,7]. For example, the feeding rate is calculated as a percentage of animal biomass and requires regular adjustment according to biomass increment. The daily feeding rates of greenlip abalone (*Haliotis laevigata*) generally range from 4.00 to 5.25% for 1-year-old and from 1.00 to 1.75% of the biomass for 2-year-old abalone [5]. Additionally, quantitative estimation of abalone biomass is also required in fishery management and resource conservation [8–11].

The current method for measuring the biomass of abalone is to physically remove animals from the attachment/substrate using a metal spatula to scoop up the abalone from the tank floor. The shell length and weight were then measured using calipers and scales [5,6,12]. However, this traditional measurement caused serious physical injury to the foot, shell and tissue as abalone adhere firmly to substrates using their muscular foot. Moreover, moving and handling abalone could cause physiological disturbances, exposure to air, further increasing stress, and significantly impact their health via depressing their immune function, leading to lower phagocytic rates and reduced antibacterial activity [13]. In some situations, anaesthetics are often used to remove abalone from the substrate to measure body weight on aquaculture farms [13,14]. However, it was reported that the anaesthetic method had the most severe effect on the health of abalone compared to those manually detached without anaesthesia [13]. Therefore, there is a need to develop an accurate, non-invasive, and cost-effective technology for measuring body mass in abalone.

Image analysis technology has been widely used to estimate fish mass in aquaculture and fisheries [15–17]. This technology encompasses image acquisition, image processing, and statistical analysis procedures [18,19]. The mass estimating method was developed based on the high correlation between length and weight of animals, as organisms biologically increase in length and weight during their development. Particularly, this correlation makes it possible to back-calculate weight using shell length [11]. The vision technology enables the measurement of animal length using 2D images, and estimated weight values are then calculated using regression models [15,16,19]. However, at present, limited information is available regarding the use of image analysis technology to predict abalone weight. Therefore, this study developed models to accurately estimate abalone weight using image-based measurements of shell length or shell area, which were used for calculating feeding rates, growth, sorting, and harvesting without causing physical stress or damage to the animals. The findings of this study could potentially facilitate the integration of artificial intelligence into abalone fisheries and aquaculture management, for instance, through automated size and weight monitoring systems.

2. Materials and Methods

2.1. Abalone Samples

The experimental greenlip abalone (1, 2 and 3 years old) were purchased from South Australian Mariculture at Boston Point in South Australia and held in a flow-through seawater system at ambient water temperature (22 ± 1 °C) at the South Australian Research and Development Institute Aquatic Science Centre (SARDI) at West Beach, South Australia.

2.2. Weight Measurement and Image Capturing

Abalone were manually removed from the aquaculture tanks and then weighed on a scale and measured shell length using a stainless steel electronic digital LCD Vernier Caliper Micrometer (150/300 mm). These data were referred to as the actual weight (g) and the actual length of the abalone (mm).

To capture the digital image of the abalone, we used a light table as described by Hoang et al. [12] (Figure 1). Two natural white bulbs were mounted on either side of the table, and a digital camera was positioned on an adjustable arm between the two lights. The camera (Canon IXUS 230HS, manufactured by Canon, Japan) was placed 25 cm above the specimen, and each digital image was captured alongside a reference colour card (X-Rite; ColourChecker®).

Figure 1. The light table and digital camera (**left**) were used to capture images of greenlip abalone (*H. laevigata*), and a reference colour card (**right**) was used to convert the pixels to length in mm.

2.3. Image Processing

Digital images were analysed using ImageJ 1.53a software (Wayne Rasband, National Institute of Health (Bethesda, MD, USA)). The protocol was previously described by Mazzoli and Favoni [20]. Briefly, image calibration is required to convert the image dimensions in pixels to known physical dimensions in millimeters (mm) using a reference card. Image processing algorithms require a binary image, which can be produced by converting original images to 8-bit images and then applying proper thresholding. This function automatically or interactively sets lower and upper threshold values, segmenting grey-scale images into features of interest and background.

2.4. Statistical and Regression Analysis

Data were analysed using the IBM SPSS statistical program (Version 22 for Windows; IBM SPSS Inc., Chicago, IL, USA). The three regressions were used in the current project as linear ($y = ax + b$), quadratic ($y = ax^2 + bx + c$) and power ($y = ax^b$) models. In these equations, y = weight (g); x = image-based shell length (mm) or shell area (mm^2); a, b, c are coefficients. The R^2 value was calculated for each equation and used to represent fitness.

Three abalone year classes were used in the current research. The actual shell length and weight of the abalone were measured manually using a scale and caliper. In contrast, the image-based shell length and area were calculated from photos using ImageJ 1.53a software (Wayne Rasband, National Institute of Health (Bethesda, MD, USA)). The data were divided into 70% and 30% for developing models and validation tests, respectively. For the first datasets, 150 of 1-year-old (weight = 4.25 ± 2.07 g, shell length = 31.44 ± 6.16 mm), 98 of 2-year-old (weight = 7.48 ± 1.13 g, shell length = 39.15 ± 2.34 mm) and 38 of 3-year-old (weight = 47.25 ± 9.42 g, shell length = 70.57 ± 5.05 mm) greenlip abalone were measured and photographed for building and determining the constants of the models, while 65 of 1-year-old (weight = 3.96 ± 2.0 g; shell length = 30.71 ± 5.50 mm), 42 of 2-year-old (weight = 7.23 ± 1.29 g, shell length = 38.72 ± 2.68 mm) and 16 of 3-year-old (weight = 51.05 ± 10.81 g, shell length = 72.57 ± 5.29 mm) animals were collected for validating the models' performance and the prediction error for the independent datasets.

The performance of algorithms was evaluated using hold-out cross-validation. The model's error values were calculated using the method described by Viazzi et al. [19]. $W_{estimated.i}$: the estimated weight of abalone from images, while $W_{actual.i}$: actual weight of abalone from manual measurement. N was the number of samples.

The root mean squared error (RMSE)

$$\text{RMSE} = \sqrt{\frac{\sum_{N}^{i=1}(W_{estimated.i} - W_{actual.i})^2}{N}}$$

The mean absolute error (MAE)

$$\text{MAE} = \frac{\sum_{N}^{i=1}|W_{estimated.i} - W_{actual.i}|}{N}$$

The mean absolute relative error (MARE)

$$\text{MARE} = \frac{\sum_{N}^{i=1} |W_{estimated.i} - W_{actual.i}|/W_{actual.i}}{N} \times 100$$

The maximum absolute error (MXAE)

$$\text{MXAE} = Max_{i=1}^{N}\left(|W_{estimated.i} - W_{actual.i}|\right)$$

3. Results

3.1. Predicting Model Development for 1-Year-Old Abalone

The regression models for weight estimation of 1-year-old greenlip abalone using the image-based shell length and shell area are shown in Figure 2. There were positive correlations between the actual weight and the image-based shell length (R^2 values ranged 0.937–0.987) and the image-based shell area (R^2 values 0.975–0.989).

Table 1 shows the error of the models for weight prediction using the image-based shell length and the image-based shell area from the test datasets (N = 150). The quadratic model performed better, with smaller error values (RMSE = 0.32, MAE = 0.25, MARE = 6.18%) for weight estimation from the image-based shell length. In contrast, the power regression model (RMSE = 0.30, MAE = 0.22, MARE = 5.18) performed better for predicting weight from the image-based shell area. The validation datasets (N = 65) also confirmed that the quadratic and power equations had a higher accuracy to estimate the weight of 1-year-old abalone from the image-based shell length (RMSE = 0.31, MAE = 0.23, MARE = 6.08%) and the image based shell areas (RMSE = 0.37, MAE = 0.26, MARE = 6.05%) than the linear model (Table 2; Figure 3).

Table 1. Error in the estimation of greenlip abalone (*Haliotis laevigata*) weight and related statistical values in test datasets using the image-based shell length and image-based shell area.

Year Class	Regressions	Error in Weight Estimation from Image-Based Shell Length						Error in Weight Estimation from Image-Based Shell Area				
		No.	RMSE(g)	MAE (g)	MARE (%)	R^2	*p*-Value	RMSE (g)	MAE (g)	MARE (%)	R^2	*p*-Value
1	Linear	150	0.52	0.41	16.29	0.937	<0.001	0.33	0.26	8.87	0.975	<0.001
	Quadratic		0.32	0.25	6.18	0.977	<0.001	0.34	0.24	5.75	0.979	<0.001
	Power		0.69	0.55	12.70	0.987	<0.001	0.30	0.22	5.18	0.989	<0.001
2	Linear	98	0.59	0.43	6.07	0.726	<0.001	0.51	0.39	5.31	0.799	<0.001
	Quadratic		0.60	0.43	6.01	0.726	<0.001	0.63	0.51	7.10	0.807	<0.001
	Power		0.60	0.43	6.02	0.716	<0.001	0.51	0.39	5.42	0.798	<0.001
3	Linear	38	2.49	1.89	4.70	0.930	<0.001	2.51	1.90	4.02	0.929	<0.001
	Quadratic		2.16	1.73	3.61	0.947	<0.001	2.34	1.78	3.72	0.938	<0.001
	Power		5.17	4.55	9.43	0.953	<0.001	2.44	1.78	3.70	0.943	<0.001
All years	Linear	286	4.72	3.74	114.17	0.898	<0.001	2.26	1.81	50.51	0.976	<0.001
	Quadratic		1.19	0.87	18.71	0.993	<0.001	1.47	0.81	8.10	0.994	<0.001
	Power		3.04	1.49	10.88	0.987	<0.001	1.95	1.04	8.76	0.988	<0.001

No.: number of animals; RMSE: The root mean square error; MAE: The mean absolute error; MARE: The mean absolute relative error; R^2: the coefficient of determination.

Table 2. Error in the estimation of greenlip abalone (*Haliotis laevigata*) weight and related statistical values in the validation datasets using the image-based shell length and image-based shell area.

Year Class	Regressions	Error in Weight Estimation from Image-Based Shell Length						Error in Weight Estimation from Image-Based Shell Area				
		No.	RMSE (g)	MAE (g)	MARE (%)	R^2	*p*-value	RMSE (g)	MAE (g)	MARE (%)	R^2	*p*-value
1	Linear	65	0.51	0.37	11.29	0.941	<0.001	0.41	0.28	7.61	0.967	<0.001
	Quadratic		0.31	0.23	6.08	0.978	<0.001	0.47	0.32	7.04	0.975	<0.001
	Power		0.74	0.59	13.82	0.983	<0.001	0.37	0.26	6.05	0.981	<0.001
2	Linear	42	0.72	0.61	8.51	0.761	<0.001	0.60	0.49	6.69	0.855	<0.001
	Quadratic		0.70	0.60	8.33	0.762	<0.001	0.47	0.37	5.27	0.871	<0.001
	Power		0.72	0.61	8.51	0.751	<0.001	0.61	0.50	6.80	0.860	<0.001
3	Linear	16	3.82	3.12	5.97	0.886	<0.001	3.76	3.03	5.87	0.889	<0.001
	Quadratic		3.85	2.95	5.59	0.887	<0.001	3.87	3.03	5.76	0.889	<0.001
	Power		6.35	5.10	9.45	0.908	<0.001	3.79	3.05	5.82	0.908	<0.001
All years	Linear	123	4.76	3.56	95.86	0.918	<0.001	2.41	1.83	45.75	0.980	<0.001
	Quadratic		1.54	0.95	15.00	0.991	<0.001	1.88	0.95	8.59	0.991	<0.001
	Power		1.84	0.98	7.65	0.991	<0.001	2.37	1.97	8.22	0.990	<0.001

No.: number of animals; RMSE: The root means square error; MAE: The mean absolute error; MARE: The mean absolute relative error; R^2: the coefficient of determination.

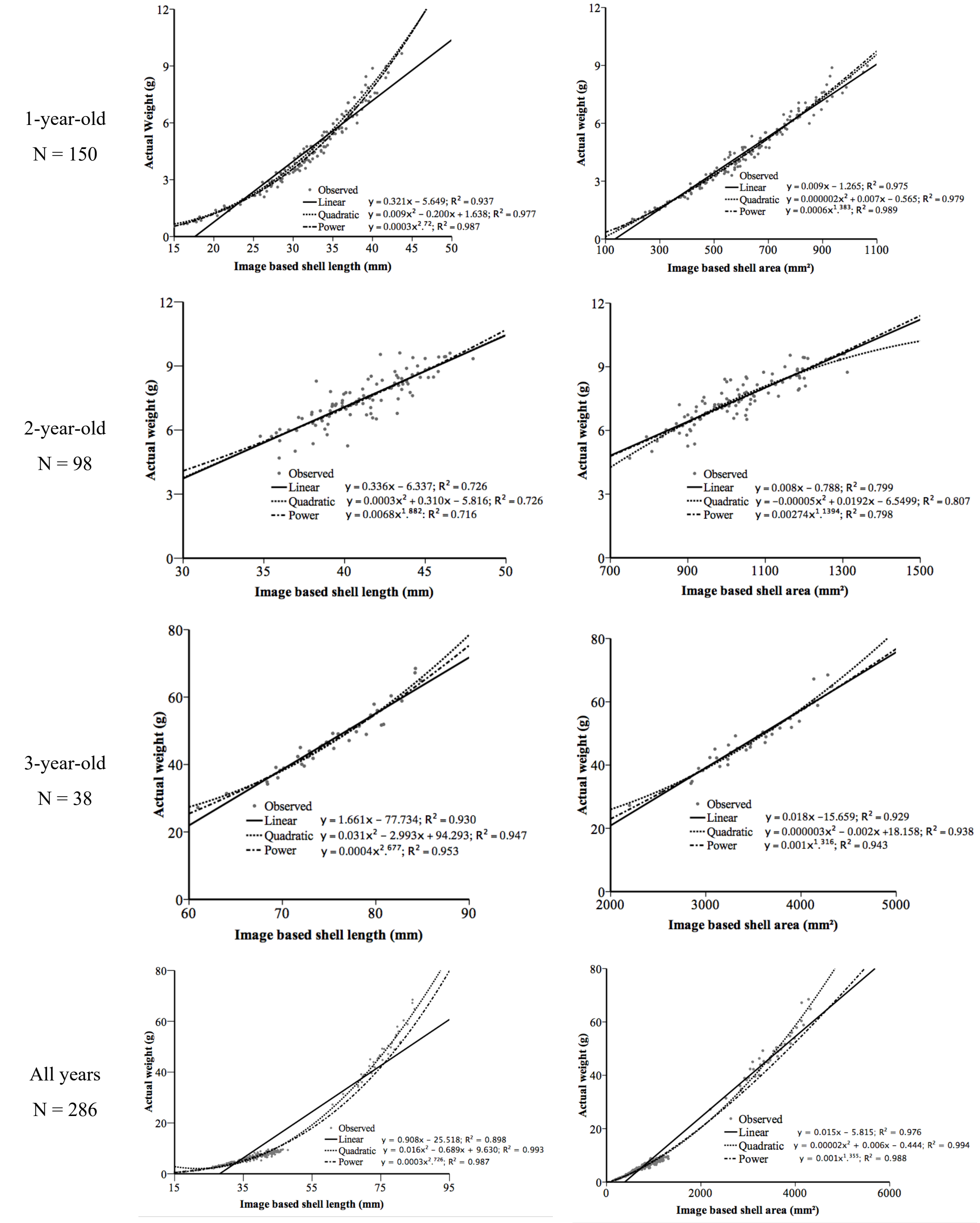

Figure 2. The predicted weight models (linear, quadratic and power equation) using image-based shell length (**left**) or area (**right**) of greenlip abalone.

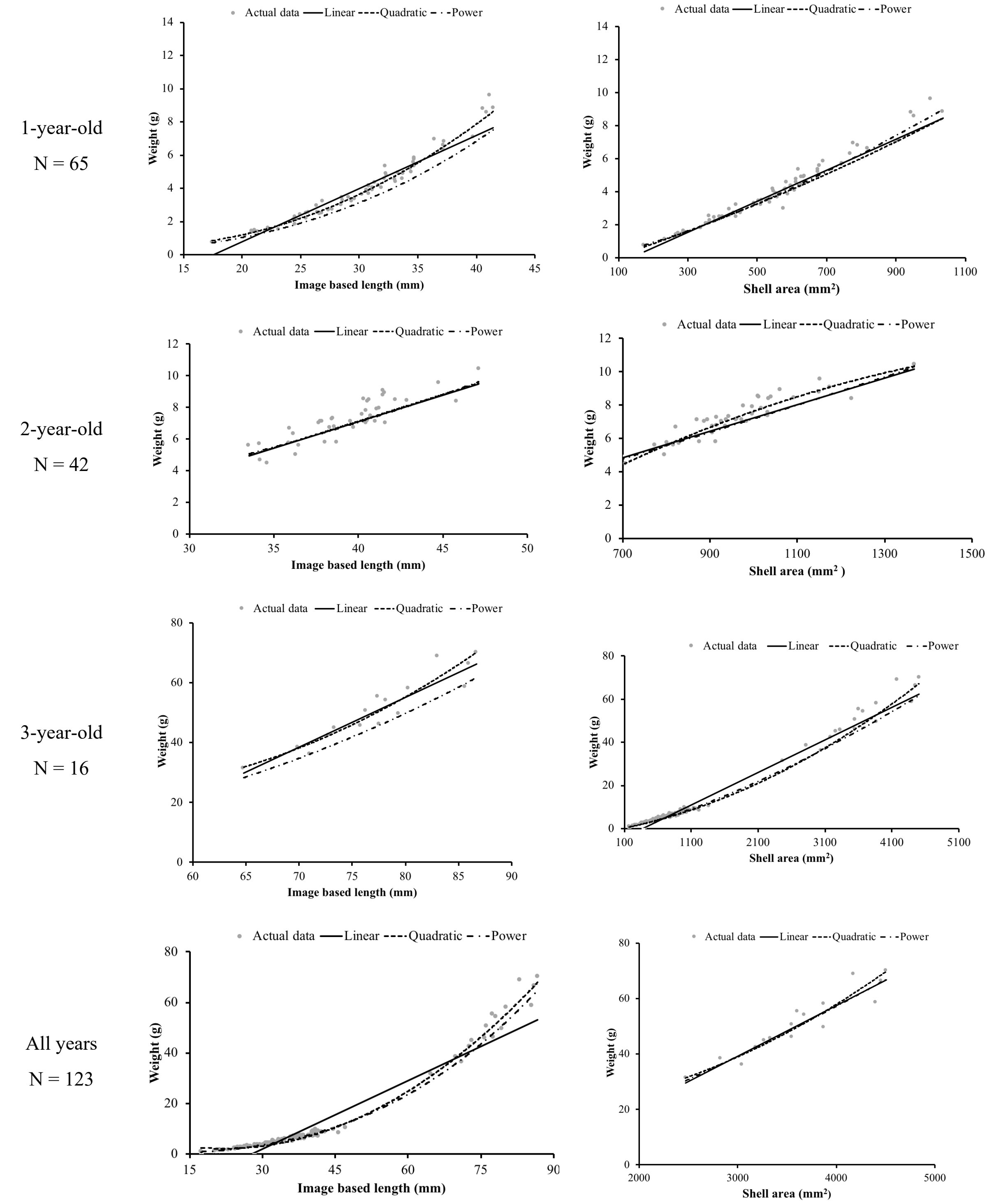

Figure 3. The estimated weight of greenlip abalone (*Haliotis laevigata*) in the validation datasets using image-based shell length (**left**) or image-based shell area (**right**).

3.2. Predicting Model Development for 2-Year-Old Abalone

The regression models for estimation of the 2-year-old greenlip abalone weight from the image-based shell length and the shell area are shown in Figure 2. The correlation coefficients (R^2 values) were similar among regression models for weight estimation using the image-based shell length (R^2 linear model = 0.726, R^2 quadratic model = 0.726 and R^2 power model = 0.716) and the image-based shell area (R^2 linear model = 0.799, R^2 quadratic model = 0.807 and R^2 power model = 0.798). In all regression models, there was a significant relationship between actual weight and image-based shell length or shell area of 2-year-old greenlip abalone ($p < 0.001$; Table 1).

The errors in estimating the weight of abalone from the image-based shell length were similar among regression models in the test datasets (RMSE = 0.59–0.60; MAE = 0.43 and MARE = 6.02–6.07%; Tables 1 and 2) and the validation datasets (RMSE = 0.70–0.72; MAE = 0.60–0.61 and MARE = 8.33–8.51%; Tables 1 and 2). For estimating the weight of abalone from the image-based shell area, the linear regression model of the test datasets performed better, with lower error values (RMSE = 0.51, MAE = 0.39, and MARE = 5.31%; Table 1) compared to other models. The quadratic model of the validation datasets had the lowest error parameters (RMSE = 0.47, MAE = 0.37, and MARE = 5.27%; Table 2; Figure 3). The quadratic model could accurately predict abalone weight from the image-based shell area.

3.3. Predicting Model Development for 3-Year-Old Abalone

The regression models for estimating the weight of 3-year-old greenlip abalone from the image-based shell length and the shell area are shown in Figure 2. The R^2 values between the actual weight and the image-based shell length or image-based shell area were more than 0.9 across all models, showing a relatively high correlation. The highest R^2 values (0.953 and 0.943) were found in the power model for both the image-based shell length and shell area, respectively.

The quadratic model was more effective in estimating the weight of abalone from either image-based shell length or shell area, as evidenced by smaller error values in both test datasets and validation datasets (Tables 1 and 2).

3.4. Model Development and Estimate Error for All Years of Abalone

The regression models for estimating the weight of the combination of all years greenlip abalone from the image-based shell length and shell area are shown in Figure 2. The correlation coefficients were relatively high across the regression models (R^2 = 0.898–0.994), showing a strong correlation between the weight and image-based shell length and shell area (Figure 2).

The error parameters in weight estimation of abalone from the image-based shell length in the test datasets (RMSE = 3.04; MAE = 1.49 and MARE = 10.88%; Table 1) and validation datasets (RMSE = 1.84; MAE = 0.98 and MARE = 7.65%; Table 2; Figure 3) confirmed that the power model was best for weight prediction. However, for estimating the weight of abalone from the image-based shell area, the power models exhibited similar performance to the quadratic model but outperformed the linear model (Tables 1 and 2).

3.5. Model Development and Estimate Error Using Validation Datasets

The results from the validation showed similar trends that were observed in models using training dataset. R^2 values ranged from 0.941–0.983, 0.751–0.762, 0.886–0.908, for year 1,2,3 abalone, respectively (Figure 3). The estimation errors were determined and reported in Table 2. The smallest MARE was recorded from quadratic models for year 1 (6.08%), year 2 (8.33%), year 3 (5.59%) and power regression (7.65%) for all years.

4. Discussion

Regular biomass assessment in abalone is important for determining feed intake, growth rate, sorting and grading, adjusting stocking density, harvesting, reproduction, and maturation. In farms, the abalone attach directly and firmly to the bottom of the concrete slab tank. To measure biomass gain, abalone are manually chipped using a metal spatula to scoop up abalone from the bottoms of culturing tanks or by applying anaesthetics to relax the adductor muscle. These procedures significantly caused detrimental effects on abalone, such as physical damage and stress, air exposure leading to metabolic constraints, reduced growth potential, and increased mortalities [5,6,12]. The non-invasive method using image processing in the current study allowed for accurate estimation of abalone biomass. At the same time, they can still attach to the tank bottom without causing any stress or damage to the animals. The mathematical regression models were successfully built and validated through an image processing method, using the actual shell length/shell area and weight of abalone across three different age groups. In general, shell area regressions provided better performance than those that were based on shell length, and particular mathematical models should be selected according to abalone age groups.

The ratio of weight to shell length is complex and it is not constant over the abalone's lifespan. The shell length grows significantly in younger abalone as they allocate energy to growth in shell length and typically display longer, thinner shells than larger, maturing individuals whose weight increases much faster in proportion to the shell [9]. Thus, particular mathematical models were developed for different year classes to obtain better predictions in current research. In general, the power regression can be applied to all year group model. The quadratic model should be considered for year 1 and year 3 abalone, while any model can be used for year 2 abalone due to similar performances.

R^2 is used to evaluate the fitness of the regression models. R^2 measures the predictive power of the regression model from the dependent variables. In the present study, R^2 values generated from all equations for all year groups ranged from 0.918 to 0.991, indicating the strong predictive ability of the regression model in abalone, which is consistent with the results of other studies [21]. For example, the R^2 value between shell length and weight of abalone generated from power regression (0.918) for all year class models was similar to the R^2 value in the study of Lee et al. [21]. In another study, 7400 abalone, *Haliotis laevigata,* were collected and measured. The results showed a significant cubic relationship and a power regression between shell length and whole body weight (R^2 = 0.941–0.966) [10]. In general, this strong correlation suggests that it is feasible to estimate animal weight from shell parameters or to back-calculate shell size from animal weight.

The length and weight relationships are also useful in a stock assessment program to estimate weight from length for predictions of weight at different size groups. It was reported that the relationship between shell length and whole weight for *Haliotis laevigata* at each of the regions was close to a cubic relationship in all 5 observing regions [10]. However, according to other studies, morphometric variation could occur among wild abalone regarding collecting locations, species, or ages that may significantly affect the relationship between shell length and weight. This conclusion was based on analysing morphometric relationships in 61 populations of *Haliotis iris* in New Zealand [8]. Similarly, an investigation was conducted on the length-weight relationship of different size groups of 390 Indian abalone, *Haliotis varia*, collected from the 'Paars' off Mandapam coastal waters of the Gulf of Mannar. The results indicate that the length-weight relationship has a reasonably good fit in medium-sized abalone (shell length of 25–35 mm, R^2 = 0.8368), but it is poor in small-sized abalone (shell length of 15–25 mm, R^2 = 0.2609) and lowest in large-sized abalones (shell length 35–45 mm, R^2 = 0.1641) [22]. Those authors suggest that the growth rate in length and weight is initially allometric and subsequently becomes isometric in medium-sized abalones and finally reverts to allometry. Current research used data from cultured abalone at different age groups, and they may not effectively perform using wild samples, as morphological variability is less in controlled environments like aquaculture facilities compared to nature. Additionally, some of the challenges associated with using this image technology in natural environments such as kelp covering, uneven surfaces, the unflattened shape of abalone, turbidity and wave action, should be taken into account for developing models.

In the current study, R^2 values (0.751–0.762) were low when the image-based shell length was used to predict weight; however, R^2 values were high (0.860–0.871) when the image-based shell area was used to predict weight in the 2-year-old group. Additionally, the correlation between the actual weight and measured shell length or area from images is statistically significant in this 2-year-old group. The estimating errors for 2-year-old animals in the validation test were smaller than those for the 1-year-old or all-sized groups when the image-based shell length or area was used to predict weight. Therefore, the results of our research suggest that no significant morphometric variation was observed in terms of size. This difference may be due to animal condition, as cultured abalone were used in the current research. In contrast, wild animals were collected in the studies of Refs. [8,22].

The development of applications is highly recommended to simplify body weight estimation from an abalone photo using image analysis techniques. Specifically, photos of abalone can be taken under the water by human or using autonomous underwater vehicle [23]. The shell length and area will be measured and converted to biomass weight using regression models. However, the reliance on a fixed light table and a specific camera setup in current research may restrict the practical adoption of this method in field settings or on commercial farms where standardized imaging equipment is not available. Future efforts could focus on developing a more flexible and portable image acquisition system to improve real-world applicability. Furthermore, improvements in sample diversity, validation rigor such as k-fold cross-validation or external validation using independent datasets sourced from different farms or geographical regions, and practical applicability are needed before the method can be widely adopted in aquaculture.

5. Conclusions

The current study demonstrates that abalone weight can be accurately estimated using a non-invasive method based on captured images, combined with image analysis. The model selection to calculate the weight from an abalone photo is dependent on size and shell parameters. The power model is recommended for predicting abalone weight using the image-based shell length analysis. In contrast, either the quadratic model or the power model can accurately estimate abalone weight from shell area analysis, regardless of size. This research indicates the feasibility of developing an automatic monitoring tool to estimate abalone body mass from photos in conjunction with image analysis.

Author Contributions

T.H.H.: significantly contributed to the conception, method, data analysis, writing original draft; D.A.J.S.: significantly made contribution in conception and provided comments for writing draft; G.L.: substaintially contributed in method, data analysis and model development; D.T.: significantly provided expertise in data analysis; H.S.: significantly contributed in method and data analysis; Y.T.: made substantially contributions in concept, method and supervision. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

The data supporting the results of this study can be obtained from the corresponding author upon reasonable request.

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Conflicts of Interest

The authors declare no conflict of interest.

Use of AI and AI-Assisted Technologies

No AI tools were utilized for this paper.

References

1. Suleria, H.A.R.; Masci, P.P.; Gobe, G.C. Therapeutic potential of abalone and status of bioactive molecules: A comprehensive review. *Crit. Rev. Food Sci. Nutr.* **2017**, *57*, 1742–1748.
2. Cook, P.A. The worldwide abalone industry. *Mod. Econ*. **2014**, *5*, 1181–1186.
3. Cook, P.A. Worldwide abalone production statistics. *J. Shellfish Res.* **2019**, *38*, 401–404.
4. Cook, P.A. Worldwide abalone production: An update. *N. Z. J. Mar. Freshw. Res.* **2025**, *59*, 4–10.
5. Stone, D.A.; Harris, J.O.; Wang, H.; et al. Dietary protein level and water temperature interactions for greenlip abalone *Haliotis laevigata. J. Shellfish Res* **2013**, *32*, 119–130.
6. Duong, D.N.; Stone, D.A.; Qin, J.G. et al. Energy budgets for Greenlip Abalone (*Haliotis laevigata* Donovan) fed graded dietary crude protein levels at seasonal water temperatures. *Aquaculture* **2021**, *536*, 736499.
7. Wu, F.; Liu, X.; Zhang, G.; et al. Effects of the initial size, stocking density and sorting on the growth of juvenile Pacific abalone, *Haliotis discus hannai* Ino. *Aquac. Res*. **2009**, *40*, 1103–1110.
8. McShane, P.E.; Schiel, D.R.; Mercer, S.F.; et al. Morphometric variation in *Haliotis iris* (Mollusca: Gastropoda): Analysis of 61 populations. *N. Z. J. Mar. Freshw. Res.* **1994**, *28*, 357–364.
9. Mundy, D.; Loneragan, N.; Admiraal, R.; et al. Estimating abalone growth and shell morphometrics on a sea ranch in South-Western Australia. *Asian Fish. Sci.* **2025**, *38*, 8–18.
10. Officer, R.A. Size limits for greenlip abalone in Tasmania. 48 Hobart: Tasmanian Aquaculture and Fisheries Institute 1999. Available online: https://data.imas.utas.edu.au/attachments/8f3aca6072c9-11dc-a82d-00188b4c0af8/North_West_Greenlip_Report.pdf (accessed on 1 March 2022).
11. Rogers-Bennett, L.; Melvin, A.S. Size differences in wild and farmed red abalone: Developing enforcement tools to combat illegal commercialization. *Calif. Fish Game* **2007**, *93*, 77.
12. Hoang, T.H.; Qin, J.G.; Stone, D.A.; et al. Colour changes of greenlip abalone (*Haliotis laevigata* Donovan) fed fresh macroalgae and dried algal supplement. *Aquaculture* **2016**, *456*, 16–23.

13. Hooper, C.; Day, R.; Slocombe, R.; et al. Effect of movement stress on immune function in farmed Australian abalone (hybrid *Haliotis laevigata* and *Haliotis rubra*). *Aquaculture* **2011**, *315*, 348–354.
14. Cornelia, G.; Gregory, A.L. Chapter 22—Anesthesia and Analgesia of Invertebrates. In *American College of Laboratory Animal Medicine, Anesthesia and Analgesia in Laboratory Animals*; 2nd ed.; Fish, R.E., Brown, M.J., Danneman, P.J.; et al. Eds.; Academic Press: Cambridge, MA, USA, 2008; pp. 535–545.
15. Balaban, M.O.; Ünal Şengör, G.F.; Soriano, M.G.; et al. Using image analysis to predict the weight of Alaskan salmon of different species. *J. Food Sci*. **2010**, *75*, E157–E162.
16. Balaban, M.O.; Chombeau, M.; Cırban, D.; et al. Prediction of the weight of Alaskan pollock using image analysis. *J. Food Sci* **2010**, *75*, E552–E556.
17. Li, D.; Hao, Y.; Duan, Y. Nonintrusive methods for biomass estimation in aquaculture with emphasis on fish: A review. *Rev. Aquac.* **2020**, *12*, 1390–1411.
18. Sun, D. *Computer Vision Technology for Food Quality Evaluation*, 2nd ed.; Academic Press: San Diego, CA, USA, 2016.
19. Viazzi, S.; Van Hoestenberghe, S.; Goddeeris, B.M.; et al. Automatic mass estimation of Jade perch *Scortum barcoo* by computer vision. *Aquac. Eng*. **2015**, *64*, 42–48.
20. Mazzoli, A.; Favoni, O. Particle size, size distribution and morphological evaluation of airborne dust particles of diverse woods by Scanning Electron Microscopy and image processing program. *Powder Technol.* **2012**, *225*, 65–71.
21. Lee, D.; Lee, K.; Kim, S. Design of an Optimum Computer Vision-Based Automatic Abalone (*Haliotis discus hannai*) Grading Algorithm. *J. Food Sci.* **2015**, *80*, 729–733.
22. Najmudeen, T.M. Biometric relationships of the Indian abalone *Haliotis varia* Linnaeus 1758 from Mandapam waters of Gulf of Mannar, south-east coast of India. *Indian J. Fis.* **2015**, *62*, 146–150.
23. Qin, J.; Ma, Z.; Li, Y. Review and Outlook for Research and Development in Aquatic Life and Ecosystems. *Aquat. Life Ecosyst.* **2025**, *1*, 2.